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Models for agroforestry and related land uses – Development and Applications

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Models for agroforestry and related land uses – Development and Applications

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Abstract

Agroforestry (AF) and related land use (LU) models are increasingly important for understanding complex interactions between ecological processes, socio-economic drivers, LU dynamics, and to support science-based decision-making for sustainable land management. Using systematically selected 103 academic articles; we trace and discuss modelling development and applications. Publications on AF modelling have increased notably since 2020, although LU modelling remains dominant. Seven model categories were identified. The results showed that optimization/economic models were the most frequent (22.3%), followed by cellular/spatially explicit (20.4%), process-based (19.4%), integrated or hybrid (15.5%), and empirical/statistical models (13.6%), while agent-based (4.9%) and machine learning models (3.9%) were less common. Methodological developments indicate a shift toward integrated frameworks incorporating ecological, economic, and social dimensions, although multi-scale integration remains limited. While many models have decision support systems (DSS) potential, only a small proportion (6%) are operationalized into formal DSS tools. Key challenges include data scarcity, inadequate validation, scale mismatches, model complexity, sensitivity to parameter choice, insufficient representation of farmer behavior and institutional factors. Specific gaps persist in validation, uncertainty handling, cross-system integration, and policy relevance. Established and emerging technologies, including GIS, remote sensing, and artificial intelligence, offer significant potential to advance model accuracy, scalability, and real-world applicability, although their combined application remains limited. Future research should enhance the quality of input data, integrate multiple model types, rigorous calibration, stronger alignment with decision-making needs, and improve stakeholder relevance. This is

crucial for advancing evidence-based policy to support resilient AF systems and sustainable LU planning under dynamic global conditions.

Keywords: agroforestry, land use/land cover, models, ecosystem, review

1. Introduction

Globally, agroforestry (AF) and related land use (LU) practices are increasingly recognized as essential pathways for achieving food security, climate change mitigation, biodiversity conservation, and improving rural livelihoods in managed landscapes, particularly in the face of growing environmental and socioeconomic pressures (Kindu et al. 2015; Critchley et al. 2023; Nandi et al. 2025). In this context, related LU practices refer to land management systems that share ecological, structural, or functional characteristics with AF, particularly through the integration or coexistence of woody perennials with crops, livestock, or other land uses, without necessarily meeting the formal definition of AF. AF systems typically integrate trees with crops and/or livestock on the same land unit (Nair et al. 2021). These multifunctional systems are widely promoted as nature-based solutions capable of contributing to a broad range of ecological, economic, and social benefits and are increasingly recognized for their potential to address societal challenges (Seddon et al. 2021) by enhancing ecosystem services, such as increasing biodiversity, improving carbon sequestration, and supporting resilient livelihoods (Knoke et al. 2009; Knoke et al. 2014; Kindu et al. 2016; Castle et al. 2022; Willmott et al. 2023). However, the multi-dimensional nature of these systems poses challenges for research, planning, and policy, particularly under conditions of global change, heterogeneous socioeconomic conditions and highly variable climatic regimes (Quandt et al. 2023; Tranchina et al. 2024; Kala 2025). Great uncertainty remains about their economic performance (Knoke et al. 2025). In addition, the complexity of tree–crop–environment interactions and the long timeframes over which AF systems evolve present specific and significant challenges for empirical evaluation alone (Calfapietra et al. 2010; Luedeling et al. 2016; Gonçalves et al.

2021). In this context, AF and related LU modelling have emerged as an essential scientific tool to understand complex interactions between ecological processes, socio-economic drivers, spatial land-use dynamics, and to support evidence-based decision-making for sustainable land management. In this review, a model is defined as a simplified representation of a real-world system or process used to analyze, explain, or predict its behavior (Kindu et al. 2018; Paut et al. 2021), whereas a tool refers to a practical method, framework, or software application used to conduct analyses or support decision-making (Yadav et al., 2024). Models may serve as tools in their own right or be integrated into broader decision-support tools to evaluate land use scenarios and inform management decisions.

To better explore the complexities, a wide range of AF and related LU models have been developed over the past decades, reflecting different disciplinary foundations and methodological approaches. They are developed with differing emphases, ranging from process-based biophysical simulations of plot-level growth and yield (Paut et al. 2021; Zanzi et al. 2021; Varela et al. 2024), optimization (Knoke et al. 2015; Knoke et al. 2016; Groß et al. 2024) to spatially explicit landscape models that examine land use change, connectivity, and trade-offs (Verburg et al. 2008; Kindu et al. 2018), and hybrid models that couple ecological, economic, and social factors (Elsawah et al. 2017). The models aim to capture key ecological processes (e.g., land use/land cover (LULC) changes, tree–crop interactions, soil nutrient dynamics), economic outcomes (e.g., profitability, market integration), and social drivers (e.g., adoption behavior, land tenure) that shape system performance (Knoke et al. 2015; Castro et al. 2018; Kindu et al. 2018; Garcia and Alamanos 2022; Leduc and Hansson 2024).

Despite the diversity of existing approaches, the literature remains fragmented, and there is substantial variation in how models represent system components, incorporate multi-scale feedbacks, and address uncertainties (Knoke et al. 2020b; Srikrishnan et al. 2022). Early models often focused on single domains (e.g., crop yield or carbon balance) with simplified

assumptions (Nair 1993; van Noordwijk and Lusiana 1999), whereas more recent frameworks increasingly integrate spatial data, agent behavior, and ecosystem service valuation (Murray-Rust et al. 2011; Kindu et al. 2018). At the same time, limitations remain in model accessibility, data requirements, validation across geographic and climatic contexts, and the incorporation of cross-scale social dynamics, especially in smallholder and data-poor regions (Kindu et al. 2018).

Given the multiplicity of models and applications, as well as the rapidly expanding and increasingly complex body of literature, a comprehensive systematic review of AF and related LU modelling is needed to clarify which models exist, how they differ and how effectively they answer key research questions. Beyond identifying existing modelling approaches, this review aims to provide a comparative basis for understanding their applicability to AF and related LU research. By synthesizing model categories, specific examples, methodological characteristics, data requirements, assumptions, strengths, and limitations, the review seeks to help researchers identify candidate approaches for particular assessment objectives and recognize when combining approaches may be necessary. The analysis also identifies gaps that can guide future model development and improve the relevance of modelling outputs for land-use planning and decision-making. Specifically, the following questions will, therefore, be addressed: (1) What AF and related LU models exist, and what is their existing knowledge, characteristics, components, data requirements, assumptions, and evolution over time? (2) How do existing AF and related LU models incorporate ecological, economic, and social factors, what are their data requirements and assumptions, levels of application, strengths and limitations, and how are they integrated into decision-support tools for policymakers and land managers? (3) What are the main challenges and research gaps in AF and related LU models, and how can future research and emerging technologies enhance their accuracy, applicability, and effectiveness?

2. Materials and Methods

Our systematic review follows the PRISMA reporting framwork (Moher et al., 2009) as a guideline (Knoke et al. 2021b; Kindu et al. 2022; Qasha et al. 2024) (Fig. 1). We searched Scopus and Web of Science (WoS) for scholarly publications published between 1990 and 2025. The search aimed to identify studies addressing AF and related LU models, including their characteristics, components, methodological development, applications, data requirements, assumptions, and limitations. The following keyword was used: (Agroforestry model* OR Land use model*) AND (Knowledge OR Existing model* OR Key characteristic* OR Model component* OR Evolution of model* OR Methodolog* OR Application* OR Strength* OR Limitation*) AND (Ecological factor* OR Economic factor* OR Social factor* OR Geographic context* OR Climatic context*) AND (Data requirement* OR Assumption* OR Scale of application* OR Difference* OR Model comparison) AND (Decision-support tool* OR Policymaker* OR Land manager* OR Implementation challenge* OR Model validation OR Gap* in modeling OR Future research OR Accuracy OR Applicability). Duplicate records retrieved from the two databases were removed before screening.

After applying a subject area filter, we screened titles and abstracts for relevance to AF and related LU models. The remaining publications were assessed in full text to determine whether they substantively addressed the review topic and provided information relevant to the research questions. The final dataset comprised 103 publications with their DOIs, listed in Supplementary Table S1.

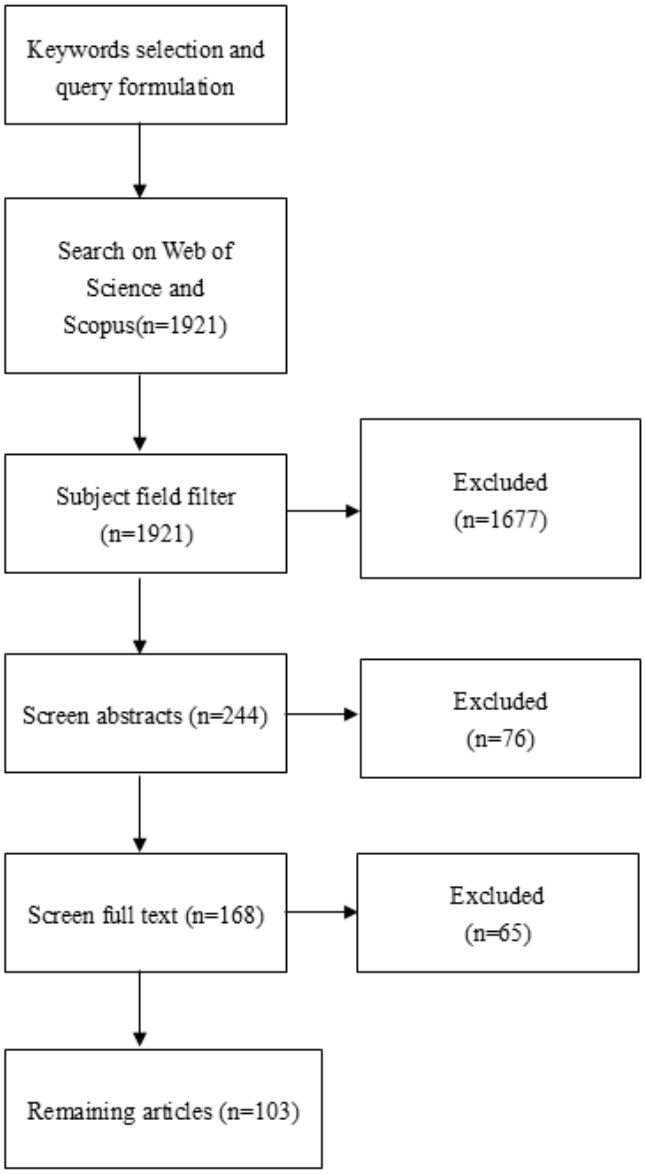


Fig. 1. Searching and screening processes in defining articles for review.

A keyword co-occurrence map was generated using VOSviewer (version 1.6.20) from the selected publications. The analysis used the full counting method to examine the co-occurrence relationships among keywords. VOSviewer grouped related keywords into colour-coded clusters based on their co-occurrence patterns. The keywords within each cluster were then examined to interpret the cluster's its main thematic focus.

Information was extracted from the 103 included publications to address the three research questions. The extracted information covered bibliographic characteristics including publication year and publication type; geographical distribution and study context; model categories and their knowledge contributions; model characteristics, components, and methodological evolution; and the ecological, economic, and social factors represented. Additional information included data requirements, assumptions, spatial scales of application, strengths and limitations, integration with decision-support systems, challenges associated with model implementation and validation, reported research gaps, future research directions, and the potential role of established and emerging technologies in AF and related LU modelling.

Both quantitative and qualitative approaches were used to analyze and synthesize the extracted information from the 103 included publications. The quantitative analysis was used to summarize the distribution of publications across the seven model categories and other descriptive characteristics reported in the review, as well as to examine keyword co-occurrence patterns. The qualitative analysis involved a comparative synthesis of the included studies, focusing on the methodological characteristics, components, applications, data requirements, assumptions, strengths, and limitations of the different modelling approaches. Reported modelling challenges, research gaps, and future directions were identified by examining and comparing the findings, limitations, and recommendations discussed in the reviewed publications. The synthesized evidence was then compared across the seven model categories to identify common challenges, differences between modelling approaches, and areas requiring further development for AF and related LU applications.

3. Results and discussions

3.1. General overview of reviewed articles

The number of publications on AF and related LU models remained relatively stable from the 1990s through the 2010s (Fig. 2). From 2020 onwards, however, annual publication numbers

increased significantly, with a particularly marked rise in AF modelling studies. This recent growth likely reflects rising global attention to sustainable land management (Scherzinger et al. 2024), climate change mitigation (Yasin et al. 2024; Edris et al. 2025; Abbas et al. 2026), and the role of AF as a nature-based solution (Awazi 2025). Despite this recent growth, LU modelling still dominates overall, with substantially more publications than AF modelling (LU = 73; AF = 30), suggesting that AF modelling remains a more specialized and still developing research domain.

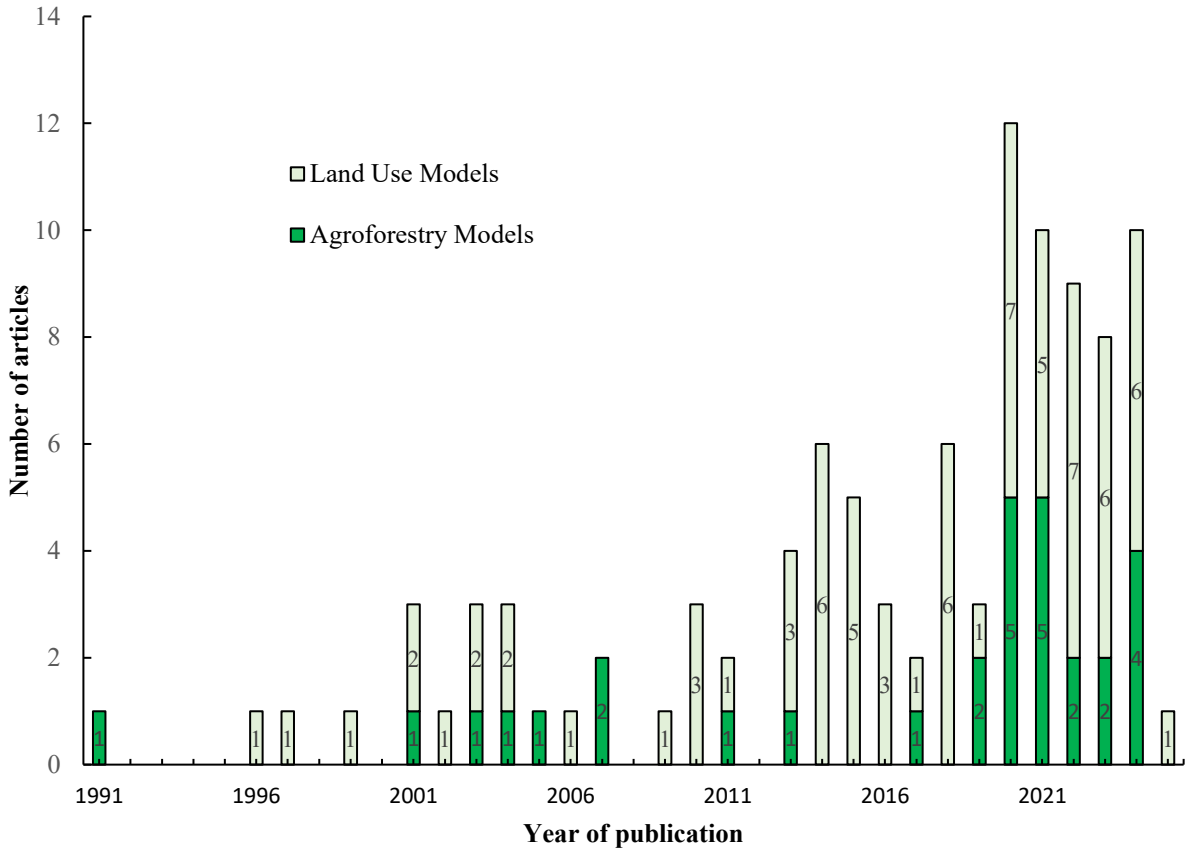
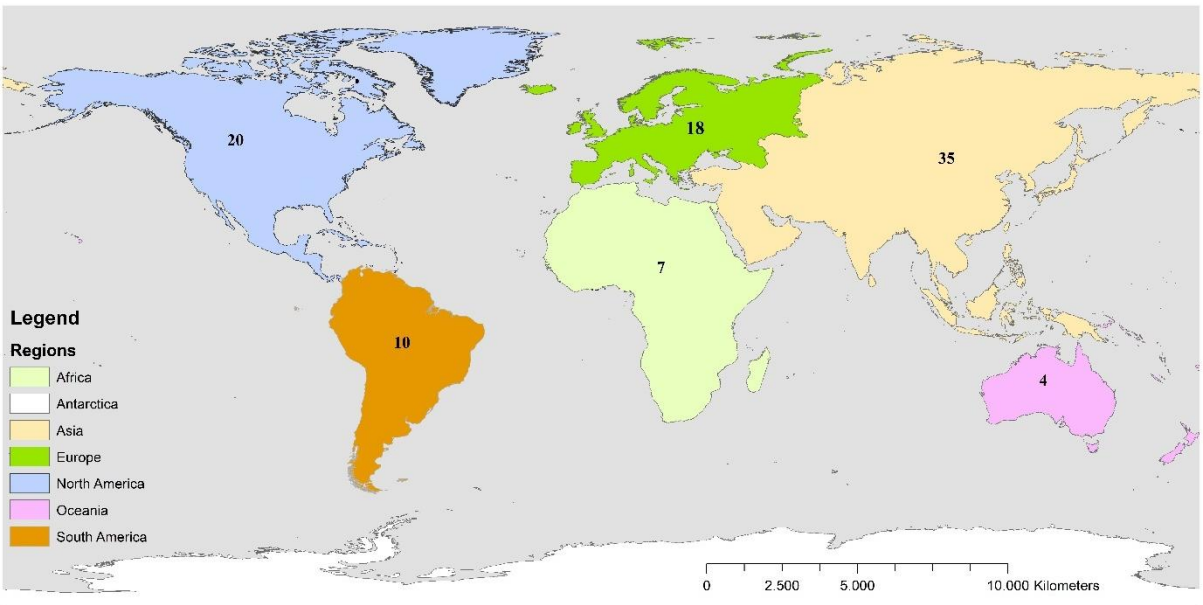


Fig. 2. Distribution of the number of reviewed articles by publication year (n = 103).

Of the 103 items analyzed, the classification "case study" was by far the most prominent, comprising 84 items (81%) (Supplementary Figure 1). In this review, a case study refers to the

196 application or evaluation of an AF or related land-use model in a specific geographical,
197 ecological, socioeconomic, or management context. Case studies are particularly relevant to AF
198 modelling because they demonstrate how models are applied to real-world systems, how local
199 conditions and data influence model outputs, and how models can inform context-specific
200 management decisions. The predominance of case studies indicates a strong emphasis on case-
201 based approaches within the dataset, suggesting that detailed, context-specific investigations
202 are the dominant methodological preference in the literature considered. The next most frequent
203 category was "mixed," with 11 items (23%). In contrast, the "review" and "experiment"
204 classifications were relatively rare, with 6 items (6%) and 2 items (2%), respectively.

205 The studies included in our sample were globally distributed across six broad regions (Fig. 3,
206 Supplementary Table S2). The largest share of articles was from Asia (34%), followed by
207 North America (19%). Europe placed third (17%), while South America accounted for 10% of
208 the studies. Fewer studies were conducted in Africa (7%) and Oceania (4%). Approximately
209 9% of the sample could not be assigned to a specific geographic region, as these studies were
210 either experimental or based on literature reviews.

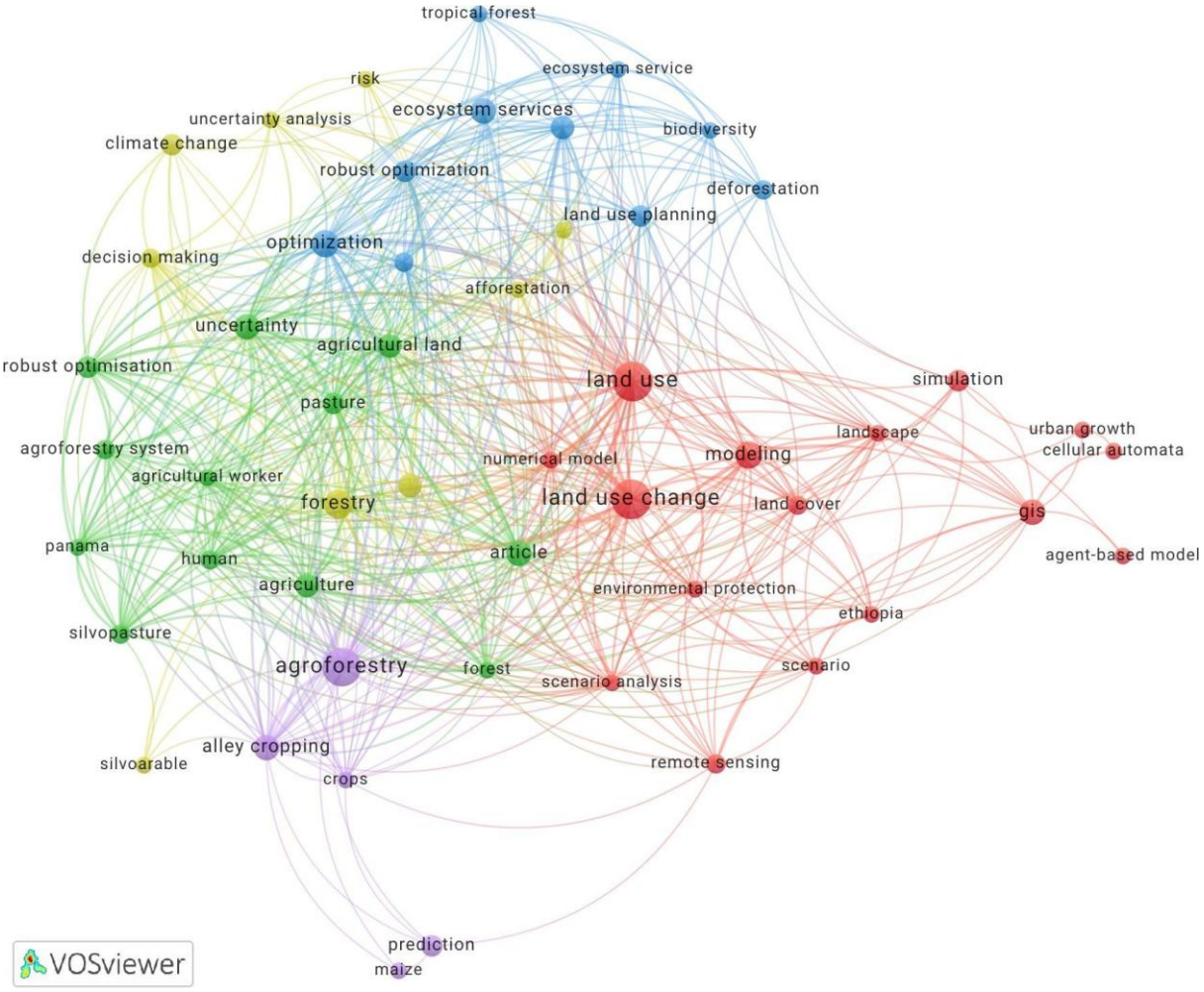


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Fig. 3 Global distribution of articles on AF and related LU models across countries (Source: base map from Esri).

Clusters of keyword co-occurrence revealed a highly interconnected thematic evolution of AF and related LU modelling research (Fig. 4). The resulting network showed five major clusters, reflecting distinct, yet interconnected research domains. These include modelling and spatial analyses, ecosystem services and biodiversity, agricultural and AF systems, optimization and decision-making, and AF practices and crop systems. The modelling cluster (red) highlights GIS, remote sensing, and simulation techniques for analyzing and predicting land dynamics, links them to scenario forecasting. The ecological cluster (blue) emphasizes biodiversity and ecosystem services, while the agriculture and AF cluster (green) highlights human-driven management and AF that focus on production systems and livelihoods. The AF practices and crop systems cluster (purple) focuses on specific AF practices and crop interactions often linked with yield prediction models. The decision making and optimization cluster (yellow) highlights the growing integration of uncertainty analyses, multi-objective optimization, and decision-support frameworks.

Overall, the findings demonstrated that AF and related LU model research are shifting toward a systems-based approach integrating modelling, ecological, and socio-economic factors for adaptive land management.



231

232

233 **Fig. 4** Bibliometric analyses network map, keywords analyses. Each node represents an item (keywords), node
234 size reflects its frequency or number of documents, and links indicate co-occurrence relations. The thickness of
235 links corresponds to the strength of these relations, while colors identify clusters of items that are more strongly
236 connected to each other than to the rest of the network. Shorter distances between nodes indicate higher
237 relatedness.

238 *3.2. Model types, characteristics, and evolution*

239 *3.2. 1. Main model types and existing knowledge*

240 The 103 reviewed studies were classified into seven model types according to their principal
241 modelling approaches (Fig. 5). The analysis focused on model types rather than individual
242 software packages or tools, as the primary objective was to compare the conceptual approaches,
243 knowledge contributions, characteristics, and applications of different modelling paradigms.

The frequency of each model type was quantified based on the number of reviewed papers in which it was identified. Optimization/economic models (23 = 22.3%) and cellular or spatially explicit grid models (21 = 20.4%) are the most frequently applied approaches, followed closely by process-based/mechanistic models (20 = 19.4%), indicating a strong emphasis on decision support, spatial allocation, and biophysical simulation. Empirical/statistical models (14 = 13.6%) remain important for identifying relationships between land-use patterns and their drivers, often relying on regression and survey-based analyses. In contrast, integrated or hybrid models (16 = 15.5%) are increasingly used to combine multiple modelling paradigms, linking spatial dynamics, biophysical processes, and decision-making components to support scenario analyses. Agent-based models (5 = 4.9%) and machine learning/data-driven approaches (4 = 3.9%) are comparatively underrepresented, suggesting limited incorporation of behavioral dynamics and advanced predictive analytics in current applications. The counts refer to reviewed papers rather than individual software packages or tools, as a single paper may employ multiple tools. Table 1 provides examples of specific models and tools identified in the reviewed studies for each of the seven model categories, alongside their key characteristics and components.

In terms of knowledge generation, the reviewed models contribute to four broad domains. First, empirical and statistical approaches generate evidence on the relationships between LU and socio-economic or environmental drivers, supporting suitability or probability assessments. Second, process-based models contribute a detailed understanding of biophysical processes, including vegetation growth, soil dynamics, and carbon sequestration, thereby supporting environmental impact assessments. Third, spatially explicit models emphasize landscape patterns and the spatial allocation of LU change, enabling scenario-based exploration of future dynamics (Mei et al. 2018; Mamanis et al. 2021; Wang et al. 2022). Fourth, optimization and agent-based approaches contribute to the analysis of LU decisions, trade-offs, and policy impacts, including economic efficiency or behavioral responses, and explicitly account for

multiple ecosystem services (Knoke et al. 2016; Knoke et al. 2020a; Reith et al. 2022). Emerging machine learning methods contribute predictive capabilities and pattern recognition, although their adoption remains limited (Varma et al. 2024). Overall, the increasing use of integrated models highlights a shift toward more holistic frameworks capable of capturing the complexity of AF systems by linking environmental processes, spatial dynamics, and human decision-making (Luo et al. 2010; Kalt et al. 2021). However, the relative scarcity of agent-based and machine learning approaches points to important gaps, particularly in representing realistic farmer behavior and leveraging large datasets to improve predictive performance (Mulia et al. 2014).

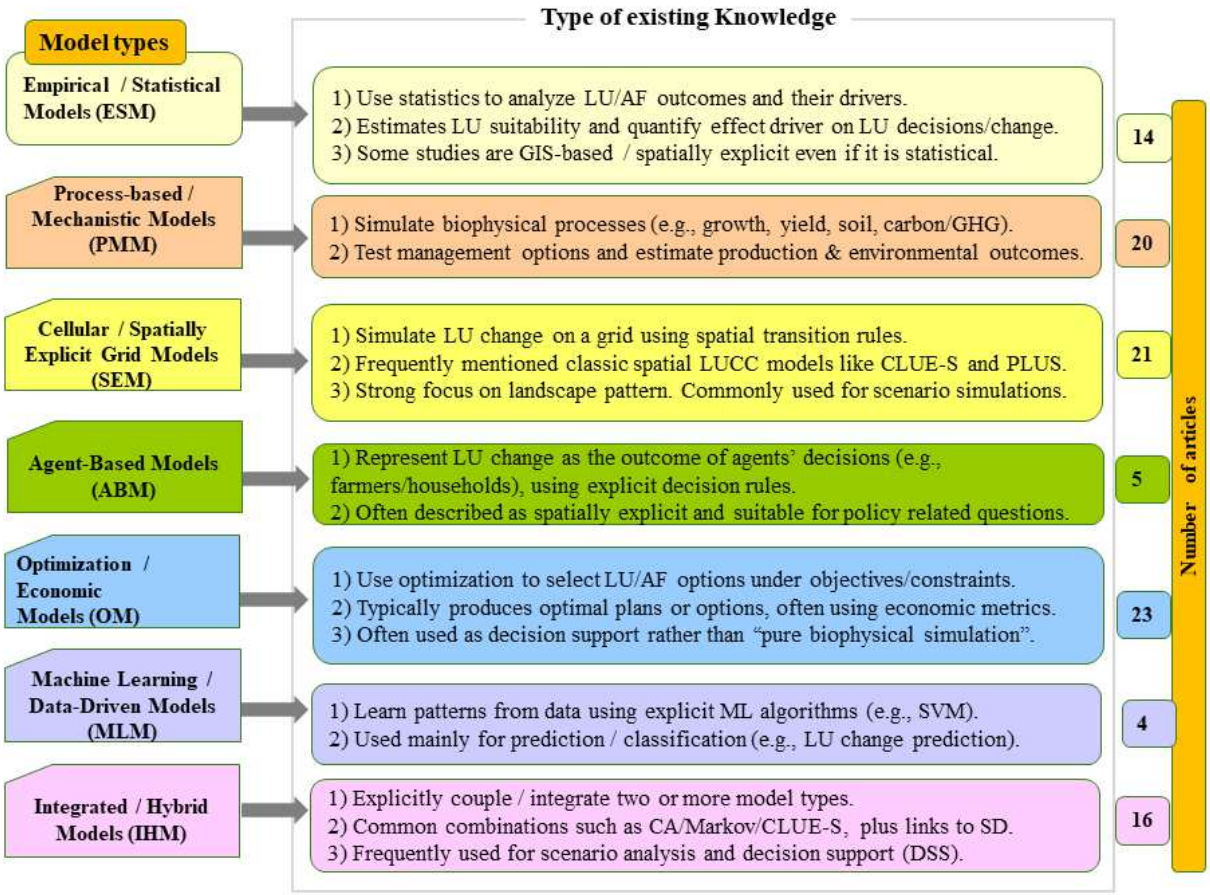


Fig. 5. Types of main AF and related LU models and their existing knowledge (n = 103)

3.2.2. Key characteristics and components of models

The reviewed modelling approaches for AF and LU systems revealed a diverse, but complementary set of characteristics and components, reflecting different analytical priorities and system representations (Table 1). These methodological differences determine the questions each approach can address and the types of outputs it can generate. Empirical/ statistical models (ESM) estimate relationships between land-use patterns and explanatory variables using observed or historical data. They can identify associations with factors such as accessibility, population, and biophysical conditions, but may provide limited representation of the underlying processes that produce LU change (Wang and Zhang 2001; Otter and Deutsch 2023). Process-based/ mechanistic models (PMM), by contrast, explicitly simulate biophysical dynamics, integrating climate inputs, soil properties, and crop–tree interactions, and are therefore particularly suitable for evaluating the productivity and environmental outcomes of AF under varying management scenarios. Cellular/Spatially explicit models (SEM) emphasize landscape patterns and allocation processes through grid-based representations and transition rules (e.g., Cellular Automata or Markov chains), enabling robust simulation of land-use change trajectories but often with simplified process representation (Han et al. 2015; Sun et al. 2016).

Agent-based models (ABM) introduce a bottom-up perspective by explicitly modelling the decision-making behavior of heterogeneous agents, such as farmers, and incorporating socio-economic and institutional factors critical for understanding AF adoption and LU dynamics (Evans and Kelley 2004; Valbuena et al. 2010). This model type is descriptive, to analyze and predict the realistic and likely behavior of land-use agents. It is specifically useful for predicting ‘business-as-usual’ land-use decisions and provides a so far underrepresented opportunity to generate counterfactual baselines as a precondition for assessing forest conservation initiatives (Knoke et al. 2023; Knoke et al. 2026). Optimization/Economic models (OM), on the other hand, focus on identifying optimal land-use configurations by balancing multiple objectives (e.g., economic returns, carbon sequestration, and biodiversity), sometimes using constraints to consider multiple uncertainty scenarios, thus, offering valuable insights for policy and land

management planning (Knoke et al. 2015; Gosling et al. 2021; Knoke et al. 2021a). This type of model generates advice to improve land-use decision-making and is thus commonly normative. Machine learning/data-driven models (MLM) leverage large datasets and advanced algorithms (e.g., Random Forest, Support Vector Machines and deep learning) to generate highly accurate predictions of land-use patterns and suitability, although they often lack interpretability and mechanistic transparency (Lee et al. 2018; Varma et al. 2024). Increasingly, integrated hybrid models (IHM) combine elements from these approaches—linking, for example, demand-driven modules with spatial allocation or machine learning components—to capture the complexity of land-use systems more comprehensively (Luo et al. 2010; Zhang et al. 2023; Zhang et al. 2024).

Across all model types, common core components include input datasets, drivers of change, model structures, and outputs. Inputs and explanatory variables may include land-use and land-cover (LULC) maps, climate and socio-economic data, accessibility, policy conditions, and environmental characteristics. Model structures range from statistical relationships and biophysical process representations to behavioral rules, spatial transition mechanisms, and optimization functions. Outputs may include land-use maps, suitability surfaces, predicted system responses, and environmental or economic indicators. The specific combination of components depends on the model's purpose and formulation. Overall, the diversity of model structures highlights the value of selecting approaches according to the research question and, where necessary, combining complementary methods to represent the multiple dimensions of AF and related LU systems.

Table 1. Summary of key characteristics and components with example tools of agroforestry and related land use models.

Model Type	Key Characteristics	Core Components	Example tools
ESM	Data-driven; estimates relationships; suitability outputs	Historical LULC data; explanatory variables;	PLS

		statistical models; suitability/probability maps	
PMM	Process-based; dynamic simulation; scenario testing	Climate inputs; soil/water/nutrients; vegetation growth; management variables; productivity outputs	Hi-sAFe
SEM	Spatial allocation; pattern-focused; transition rules	Raster maps; CA/Markov rules; spatial drivers; land-use maps	CLUE-S, PLUS
ABM	Decision-based; agent heterogeneity; scenario analysis	Agents; decision rules; environment; land-use decisions	Regional land-use ABM implemented in NetLogo
OM	Optimization; indicators; trade-offs; objective-driven	Objective functions; constraints; economic parameters; optimal allocation	Farm-SAFE
MLM	Prediction-focused; pattern recognition	Training data; predictors; ML algorithms; suitability maps	Random Forest, CNN
IHM	Integrated; multi-model coupling	Coupled sub-models; shared inputs; cross-model outputs; integrated scenarios	SD–CLUE-S integrated modelling framework

ESM = Empirical / Statistical Models, PMM = Process-based / Mechanistic Models, SEM = Cellular / Spatially Explicit Grid Models, ABM= Agent-Based Models, OM = Optimization / Economic Models, MLM = Machine Learning / Data-Driven Models (IHM) = Integrated / Hybrid Models. PLS = Partial Least Squares, CLUE-S = Conversion of Land Use and its Effects at Small regional extent, PLUS = Patch-generating Land Use Simulation, CNN = Convolutional Neural Network, SD = System Dynamics. Hi-sAFe and Farm-SAFE are model names, NetLogo is the modelling platform used for the regional land-use ABM.

3.2.3. Evolution models in methodology and application

Across the 103 studies, model development showed a general movement away from standalone, deterministic, and locally framed applications toward workflows that address uncertainty, compare multiple scenarios, and link processes across scales through explicit model coupling (Fig. 6).

Empirical and statistical studies increasingly expand from applying established adoption or suitability frameworks to using broader constructs and more structured estimation and calibration approaches that reduce reliance on heuristic parameter choices (Pontius et al. 2001; Calvin et al. 2022; Otter and Deutsch 2023). Their applications are also moving beyond driver description toward knowledge structuring and planning-oriented use cases that require explicit

links to decision or transport-related contexts (Verburg et al. 1999; Han et al. 2015; Mei et al. 2018).

Cellular and spatially explicit grid models are evolving from early spatial allocation logic toward stronger representations of demand-allocation consistency and improved transition discovery, including explicit combinations of demand components with spatial allocation procedures and refinements in calibration and rule learning (Conde Salazar et al. 2021; Sahebgharani et al. 2024).

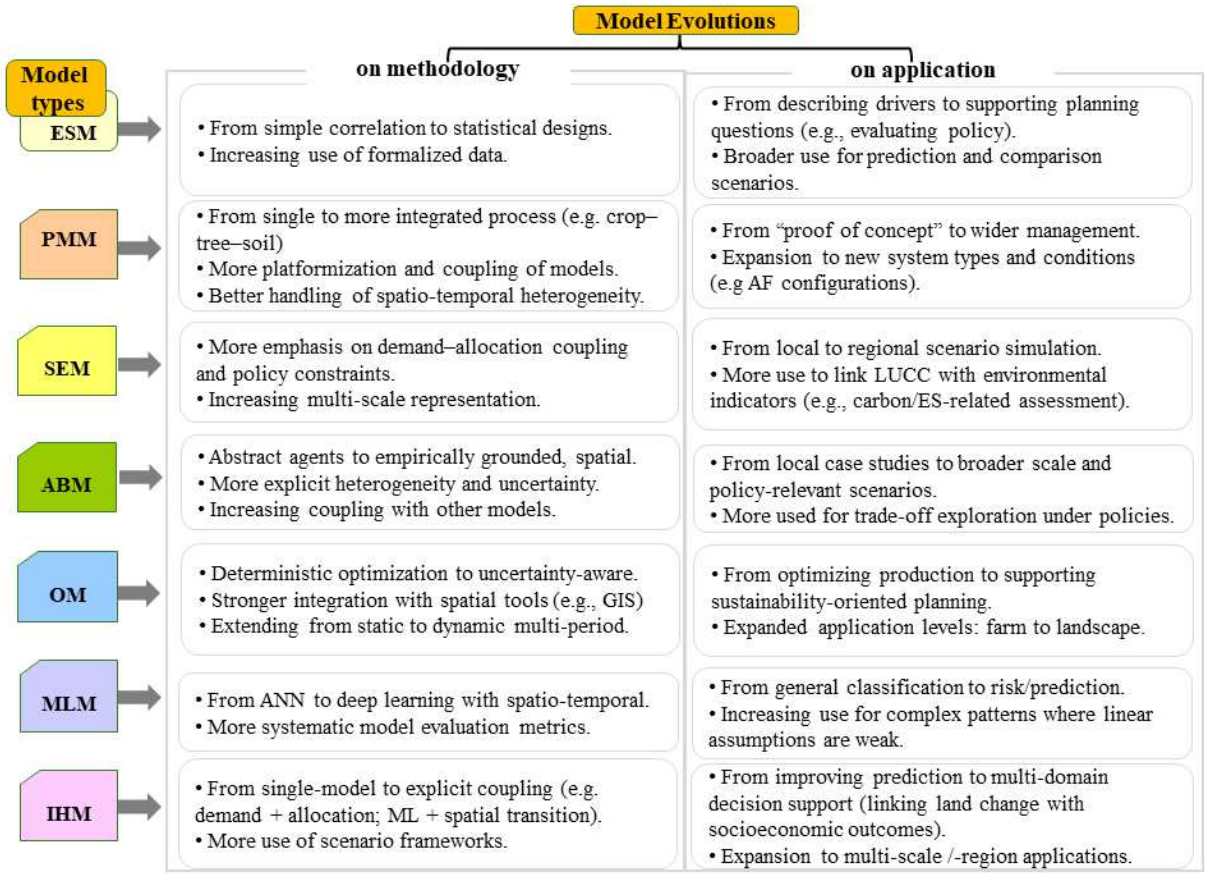
More recent developments emphasize patch-level simulation and multi-scenario control, and they increasingly align with macro-to-micro scenario settings that connect climate and socio-economic trajectories to spatial land-use patterns (Liu et al. 2024; Zhang et al. 2024).

Process-based and mechanistic AF models show methodological evolution through deeper integration of processes and components, including explicit representations of shelterbelt microclimate effects, coupled tree–crop process modules and two-dimensional representations of tree–crop interactions in newer platforms (Smethurst et al. 2017; Dupraz et al. 2019). Applications broaden from isolated mechanistic demonstrations to management- and system-design settings where alternative agroforestry configurations and interventions are evaluated under field-calibrated conditions (Dilla et al. 2020; Varela et al. 2024).

Optimization and economic models increasingly move from deterministic selection toward robust and uncertainty-aware formulations, including dynamic multi-period settings and explicit uncertainty propagation through simulation-based approaches, often combined with spatial decision support (Knoke et al. 2015; Budău et al. 2023).

ABM and machine-learning studies show parallel upgrading, with ABMs placing stronger emphasis on calibrated, spatially explicit representations of heterogeneous decision-making (Evans and Kelley 2004), and machine learning is shifting from earlier neural-network land-

373 change prediction toward deep learning architectures and hybrid workflows that connect
374 learning-based prediction with spatial simulation (Lee et al. 2018; Applegate et al. 2022).



375

376 **Fig. 6.** Evolutions of agroforestry and related land use models over time in terms of methodology and application.
377 ESM = Empirical / Statistical Models, PMM = Process-based / Mechanistic Models, SEM = Cellular / Spatially
378 Explicit Grid Models, ABM= Agent-Based Models, OM = Optimization / Economic Models, MLM = Machine
379 Learning / Data-Driven Models (HM) = Integrated / Hybrid Models.

380

381 *3.3. Integration, data, scale, performance, and decision linkages*

382 *3.3.1. Integration of ecological, economic, and social dimensions in models*

383 The distribution of studies indicated a clear shift toward integrated modelling approaches in AF
384 and related LU systems (Fig. 7). Most of the reviewed articles incorporated ecological,
385 economic, and social dimensions simultaneously, reflecting the growing adoption of holistic
386 frameworks. In contrast, models that integrate only two dimensions were less prevalent, with
387 ecological–economic combinations occurring more frequently than ecological–social or
388 economic–social pairings. This pattern suggests that economic considerations are more often

linked with ecological processes, particularly in relation to productivity, profitability, and ecosystem service valuation (e.g., Kindu et al. 2016; Munthali et al. 2023). Single-dimensional models are comparatively rare, although ecological-only approaches still appear more frequently than those focusing solely on economic or social aspects, while social-only or cultural models are notably scarce. This imbalance is consistent with broader critiques in AF and related LU research that highlight the limited integration of, for example, social and institutional dimensions (e.g., Zhao et al. 2026). Overall, these findings demonstrate that although AF and related LU modelling are increasingly aligned with integrated sustainability perspectives, social factors remain underrepresented unless embedded within fully comprehensive frameworks, underscoring the need for more explicit incorporation of human and governance dimensions in future model development.

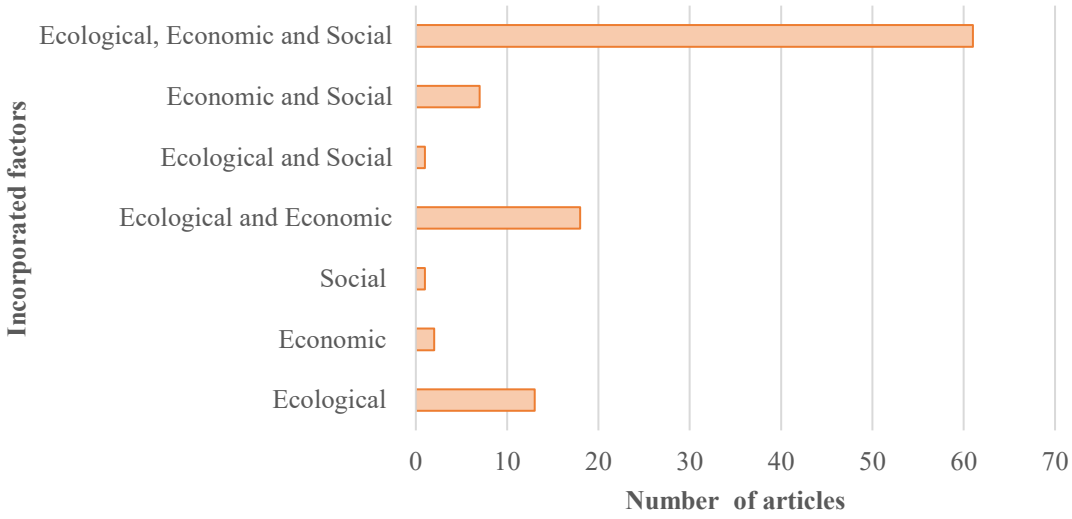


Fig. 7. Distribution of reviewed agroforestry and related land use models by incorporating ecological, economic, and social factors

3.3.2. Main data requirements and assumptions of models

The data requirements and assumptions summarized in Table 2 have important implications for modelling AF and related LU systems. Data requirements are primarily determined by the

models' representation of land systems, and assumptions commonly concern the stability of relationships, the acceptability of simplified processes, and the use of externally defined scenario settings (Verburg et al. 2004). The availability and resolution of these data therefore influence which aspects of AF systems can be assessed and how reliably alternative management and LU scenarios can be evaluated.

Empirical and statistical models typically assume a predefined functional form (e.g., logistic or nested logit relationships) and treat predictors as independent, often spatially fixed, observed comparisons or stated intentions represent reality, and conversions are restricted by predefined rules (Conde Salazar et al., 2021; Sahebgharani et al., 2024). They typically depend on extensive datasets (Table 1). Conversely, process-based and mechanistic approaches generally require more detailed biophysical and management inputs. They frequently assume transferability of mechanistic structure and parameters from prior studies, accept simplified process representations, and treat management and microclimate settings as predefined scenario inputs (Dilla et al., 2020; Easterling, 1997; Smethurst et al., 2017).

Cellular and spatially explicit grid models rely on multi-temporal LU maps, and explanatory variables. They commonly assume fixed conversion rules and neighborhood effects, stable driver–land relationships over the simulation period, and restrictions in protected or constrained areas under scenario trajectories (Han et al., 2015; Liu et al., 2024; Verburg et al., 1999). ABMs, by comparison, assume that agents follow specific and commonly stylized decision rules, land being represented as plots or cells, where exogenous scenarios define boundary conditions, while allowing heterogeneous intentions, 'good-enough' decision-making (Findlater et al. 2019), alongside socioeconomic and environmental context data (Dai et al., 2020).

Optimization and economic models require input data such as yields, costs, prices, discount rates, land-use activity data, biophysical suitability information, indicator scores, uncertainty

parameters, and expert inputs, depending on their formulation. They assume decision-makers optimize objectives under constraints, weights and scoring rules are fixed, and prices or discount rates are scenario-specific constants, with uncertainty handled through scenario sets or simulation-based settings when reported (Knoke et al., 2015; Reith et al., 2020). Machine-learning models, in contrast, require training LULC maps or time series and feature layers that combine proximity, environmental, and socio-economic predictors, and they assume reliable historical patterns that are learnable from the available data (Ghosh & Das, 2020; Ha et al., 2016). Finally, integrated and hybrid models require shared LU maps and driver layers across modules, socio-economic trajectories, and additional biophysical or assessment databases when biophysical or life cycle assessment (LCA) components are coupled, and they assume internal consistency between coupled parts and externally defined scenario pathways (Ding & Achten, 2022; Zhang et al., 2023).

These differences affect the suitability of each approach for particular AF and related LU research questions. Overall, the comparison highlights a key trade-off: models with strong theoretical assumptions (e.g., mechanistic or economic models) require detailed, high-quality input data, whereas data-driven approaches (e.g., statistical and machine learning models) rely less on explicit assumptions but demand extensive datasets for calibration and validation. This underscores the importance of aligning model choice with data availability, system complexity, and research objectives in AF and related LU studies. In addition to quantitative data, qualitative and other non-statistical information can be important for representing the social and institutional dimensions of AF and related LU systems. Such information may include farmers' knowledge and experiences, perceptions, preferences, and local contextual knowledge. These data can help explain LU decisions, the adoption of agroforestry practices, and differences in management strategies that may not be fully captured by biophysical or economic indicators alone. However, incorporating qualitative information into modelling frameworks can be challenging because it often requires systematic interpretation, categorization, or translation

459 into model parameters and decision rules. Mixed-methods approaches that combine quantitative
460 data with qualitative evidence may therefore provide a more comprehensive understanding of
461 AF systems, particularly when ecological processes, economic outcomes, and farmers'
462 decisions need to be considered together.

463 **Table 2.** Summary of main data requirements and assumptions of agroforestry and related land use models.

Model type	Assumptions	Data requirements
ESM	Functional form assumed valid; predictors treated as independent, sometimes with fixed spatial weights; observations/surveys/plots assumed to reflect reality; conversions constrained by predefined rules.	Historical LULC maps; socio-economic and demographic data; spatial drivers and constraints; some cases field, tree, or survey measurements
PMM	Mechanistic structure and parameters assumed transferable; simplified processes (no zone fluxes, limited nutrients/microclimate, restricted tree types); predefined management and scenarios (operations, climate change cases).	Weather/climate (radiation, temperature, rainfall); soils (water, C–N, pH); vegetation/stand (LAI, structure, density, traits); management (planting, thinning, pruning, fertilization, irrigation, harvest).
SEM	Land-use change follows scenario trajectories and fixed conversion rules/probabilities; assumes stable driver–land relationships; uses neighborhood effects, conversion matrices, and ordering; constrained by protected areas.	Multi-temporal land-use maps; biophysical and accessibility drivers (DEM, slope, soil, climate, roads, rivers, centers); socio-economic data (census/yearbooks, demand); policy constraints (protected areas, conversion rules/matrices).
ABM	Agents follow decision rules; assume utility maximization/satisficing under constraints; land as plots/cells; landscape often static within runs; scenarios define conditions; heterogeneous intentions	Surveys/census for agents; land cover/ownership/topography maps; economic time series (prices, wages, productivity); observed forest/tree loss or carbon data.
OM	Decision-makers optimize objectives (profit/NPV/scores) under constraints; fixed weights, prices, and discount rates; uncertainty via scenarios/Monte Carlo/robust methods; often simplified or static time horizons.	Yields, costs, prices, discount rates; land-use/area data; biophysical/suitability layers; expert/AHP scores; scenario/uncertainty parameters
MLM	Historical LULC for training; learnable patterns (CNN–LSTM); distance-decay for proximity effects.	Training LULC time series/maps; feature layers (proximity, environmental, socio-economic: population, income, unemployment.
IHM	Coupled modules assume internal consistency (demand–suitability–transition links); scenarios externally defined (population, productivity, development).	Historical LULC + RS/GIS drivers; socio-economic variables (population, GDP); process inputs (weather, soil, management); optional assessment tools/databases (e.g., LCA).

ESM = Empirical / Statistical Models, PMM = Process-based / Mechanistic Models, SEM = Cellular / Spatially Explicit Grid Models, ABM= Agent-Based Models, OM = Optimization / Economic Models, MLM = Machine Learning / Data-Driven Models (IHM) = Integrated / Hybrid Models.

3.3.3. Scale of model applications

The distribution of AF and related LU model applications revealed a clear dominance of studies conducted at finer spatial scales (Fig. 8). Most models are applied at the local (plot) level (39 = 37.9%), highlighting a strong emphasis on understanding field-scale biophysical processes, such as tree–crop interactions, soil nutrient dynamics, and productivity outcomes, which are typically best captured through site-specific analyses (e.g., Graves et al. 2011; Dilla et al. 2020). Regional-scale applications (33 = 32%) also constitute a substantial proportion of the literature, reflecting increasing attention to landscape planning, ecosystem service assessments, and policy-relevant evaluations, as emphasized in broader land-use frameworks (e.g., Ha et al. 2016; Guo et al. 2024). In contrast, landscape-scale studies (12 = 11.7%) are less common, suggesting comparatively limited integration of spatial heterogeneity and ecological connectivity, despite their recognized importance in sustainable land management (e.g., Kindu et al. 2018; Ghosh and Das 2020). Applications at national (5 = 4.9%), global (4 = 3.9%), and continental scales (2= 1.9%) remain scarce, likely due to increasing data demands, scaling uncertainties, and methodological complexity associated with extrapolating fine-scale processes to broader extents, as noted in global assessment efforts (e.g., Intergovernmental Panel on Climate Change reports). A limited number of studies employ mixed-scale approaches (8 = 7.8%), indicating that integrative, cross-scale modelling frameworks are still emerging. In this review, spatial scales are distinguished according to the extent and purpose of the analysis. The local scale refers to individual farms, fields, or AF plots and typically focuses on management practices and tree–crop interactions. The landscape scale encompasses spatially heterogeneous areas comprising multiple land uses and ecological features, with an emphasis on spatial configuration, connectivity, and interactions among land-use components. The

regional scale refers to larger geographical or administrative areas and is commonly used to examine land-use allocation, broader environmental patterns, and policy-related scenarios. These categories are indicative rather than rigid, as their spatial extents depend on the objectives and context of individual studies. Overall, these findings demonstrated that AF and related LU modelling remain predominantly grounded in site-specific contexts, with a marked decline in application as spatial scale increases. This highlights a critical research gap, underscoring the need for more robust multiscale modelling approaches to effectively link local processes with regional-to-global outcomes and to better support policy development, climate change mitigation and sustainable land-use planning.

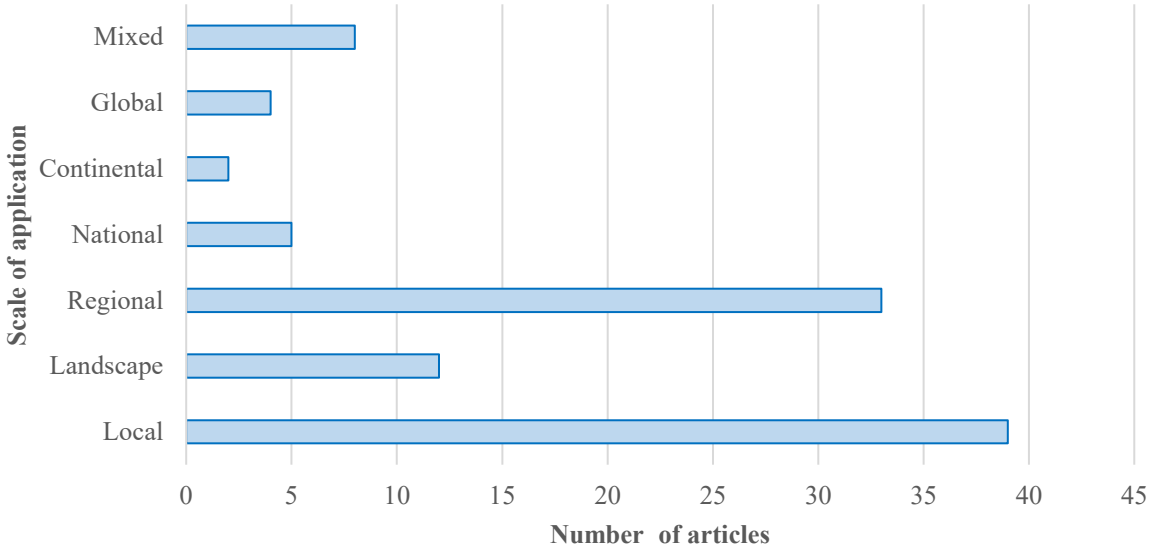


Fig. 8. Distribution of reviewed agroforestry and related land use models by scale of applications.

3.3.4. Strengths and limitations of models

The review revealed distinct but complementary strengths and limitations across model classes in representing AF and related LU systems (Table 3). These differences are particularly relevant to AF because the co-occurrence of trees and crops, interactions among ecological and socioeconomic processes, and long-term changes in system productivity pose specific challenges for modelling. Empirical and statistical models are widely valued for their data-

509 driven estimation of driver–response relationships, offering flexibility, transparency, and the
510 ability to incorporate socioeconomic variables and local knowledge; however, they often
511 oversimplify complex AF systems, remain constrained by data quality, and provide limited
512 spatial and process-level insights (Wang and Zhang 2001; Jahel et al. 2018; Conde Salazar et
513 al. 2021). In contrast, process-based or mechanistic models explicitly simulate biophysical
514 interactions such as water, nutrient, and microclimate dynamics, enabling detailed analyses of
515 system responses to management and environmental stressors, though their application is
516 frequently hindered by high data requirements, computational demands, and limited validation
517 across diverse conditions (Meiyappan et al. 2014; Dupraz et al. 2019; Dilla et al. 2020).
518 Spatially explicit grid models enhance the representation of landscape heterogeneity and spatial
519 dynamics by integrating of GIS and remote sensing data, yet they may generate fragmented
520 outputs, rely on static assumptions, and inadequately capture socioeconomic processes (Luiten,
521 2003; Wang et al., 2022).

522 Agent-based models (ABMs) provide a powerful framework for representing individual
523 decision-making, heterogeneity, and bottom-up system dynamics, making them particularly
524 useful for policy analyses and scenario exploration; nevertheless, their application is often
525 limited by data intensity, difficult interpretation of outcomes, calibration challenges, and
526 difficulties in scaling beyond local contexts, resulting in problems with generalization (Evans
527 and Kelley 2004; Valbuena et al. 2010; Dai et al. 2020). Similarly, optimization and economic
528 models are effective for identifying optimal land-use strategies and trade-offs under constraints,
529 incorporating uncertainty and expert knowledge. While sensitivity to objectives, preferences,
530 and uncertainty is an inherent and often desirable property of such models, their outputs may
531 nevertheless depend strongly on underlying assumptions and may lack spatial explicitness or
532 introduce bias (Knoke et al. 2023). More recently, machine learning approaches have
533 demonstrated strong capability in capturing complex, nonlinear relationships and improving
534 predictive performance, although their “black-box” nature, risk of overfitting, and dependence

535 on large, representative datasets limit interpretability and broader applicability (Ha et al. 2016;
536 Ghosh and Das 2020; Varma et al. 2024).

537 Integrated or hybrid models attempt to overcome these limitations by combining biophysical,
538 socioeconomic, and spatial components within a unified framework, thereby supporting holistic
539 system analyses and multi-objective decision-making; however, they remain complex, data-
540 intensive, and difficult to validate and operationalize, particularly for non-specialist users (Ellis
541 et al. 2004; Ding and Achten 2022). Overall, the evidence highlighted a fundamental trade-off
542 between model realism, interpretability, and data requirements, with direct implications for
543 representing AF and related LU systems. Models that simplify system processes may overlook
544 tree–crop interactions, changes in productivity over time, or trade-offs between economic
545 returns and ecosystem services, whereas more comprehensive models often require detailed
546 data that are unavailable across many AF contexts. Model selection should therefore reflect the
547 specific AF system, the processes and outcomes of interest, and the availability of appropriate
548 data. Integrated or hybrid approaches may help connect ecological, spatial, and socioeconomic
549 dimensions, although their value depends on adequate data integration, validation, and practical
550 applicability.

551 **Table 3.** Summary of strengths and limitations of AF and related LU use models.

Model type	Strengths	Limitations
ESM	Estimate driver effects; integrate socioeconomic drivers and local knowledge; flexible and transparent	Oversimplifies decisions; data limits reliability; weak local detail; sometimes prototype-based evidence
PMM	Represent processes and interactions; simulate responses; some capture spatial variability; provide detailed outputs	Limited validation; computationally demanding; input dependent; complex and less interpretable
SEM	Spatially explicit; integrates RS/GIS and drivers; models patch dynamics; supports scenario simulation and sometimes coupling; can improve allocation accuracy	May produce fragmented patterns; assume fixed driver–land use relations; limited socioeconomic factors; lack feedback; sensitive to parameters and data quality
ABM	Capture bottom-up decision-making; include agent heterogeneity; support policy trade-offs; sometimes spatially explicit and multi-scale	Often limited to local scales; data and calibration dependent; scaling causes aggregation issues

OM	Provide optimal plans under constraints; handle multi-objective trade-offs; include risk/uncertainty; sometimes integrate spatial factors and extreme events	Some require large data; sensitive to assumptions; often not spatially explicit; cannot capture configuration dynamics; expert reliance may bias results; limited validation for complex setups
MLM	Learn complex patterns; capture spatio-temporal dynamics; can work with limited data; may quantify factor importance	Some limited local or regional predictions; some require high data and compute demands; potential overfitting; limited handling of absence data; sometimes low interpretability
IHM	Combine complementary modules; integrate biophysical, economic, and social data; support scenario and multi-objective assessment; enable multi-scale application; can improve assessment accuracy and regional representation	Complex and data-intensive; high input uncertainty; limited transferability beyond original contexts; weak social representation; limited usability for non-experts

552 ESM = Empirical / Statistical Models, PMM = Process-based / Mechanistic Models, SEM = Cellular / Spatially
553 Explicit Grid Models, ABM= Agent-Based Models, OM = Optimization / Economic Models, MLM = Machine
554 Learning / Data-Driven Models (IHM) = Integrated / Hybrid Models.

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556

557 *3.3.5. Integration of models with decision-support systems*

558 The distribution of studies (Fig. 9) shows a limited and uneven integration of AF and related
559 LU models with decision-support systems (DSS) for policymakers and land managers. Only a
560 small proportion of the reviewed literature (6%) demonstrated explicit linkage to formal DSS
561 frameworks (Budău et al., 2023; Ellis et al., n.d.; Graves et al., 2005; Hoffhine Wilson et al.,
562 2003; Reith et al., 2020; Yadav et al., 2024), indicating that direct operationalization of models
563 into decision-making platforms remains rare. In contrast, nearly half of the studies (49%) have
564 the potential to inform planning and decision making. These studies generate outputs relevant
565 to policy and management but are not translated into structured, user-oriented tools. Within this
566 second group, dynamic land-use simulation and integrated SD–CLUE/CLUE-S models are
567 prominent, providing spatially explicit scenario outputs for regional and local land-use planning
568 (Luo et al. 2010), while several optimization and robust portfolio models are explicitly framed
569 as tools to explore land-use portfolios and trade-offs for decision-makers (Knoke et al. 2015;
570 Reith et al. 2020; Jarisch et al. 2022). Process-based and AF-specific tools such as AOBRA,
571 SimForGan and coupled Yield-SAFE/Farm-SAFE are also described as supporting resource
572 management and providing evidence useful for farmers and policymakers, but without being

packaged as full DSS platforms (Graves et al. 2007; van der Werf et al. 2007; Varela et al. 2024).

Additionally, a substantial share of papers (45%) made no reference to decision-support applications, highlighting a persistent gap between model development and practical implementation. Collectively, these findings suggest that while AF research increasingly produces decision-relevant insights, its integration into actionable DSS remains underdeveloped. This underscores the need for stronger alignment between model design and end-user requirements, as well as enhanced collaboration among researchers, practitioners, and policymakers to facilitate the transformation of analytical models into accessible and functional decision-support systems.

Beyond the technical integration of models into DSS, effective application in AF and related LU planning also depends on engagement with relevant stakeholders and decision-makers. Farmers, land managers, extension services, researchers, and policymakers may have different objectives, priorities, and information needs. Their involvement can help define relevant modelling questions, identify locally appropriate assumptions and scenarios, and interpret model outputs in relation to practical management and policy decisions. Transdisciplinary approaches that connect researchers with stakeholders throughout the modelling process may therefore strengthen the relevance, accessibility, and practical use of modelling results. This is particularly important in AF and related LU systems, where decisions often involve trade-offs among ecological performance, economic returns, and social priorities.

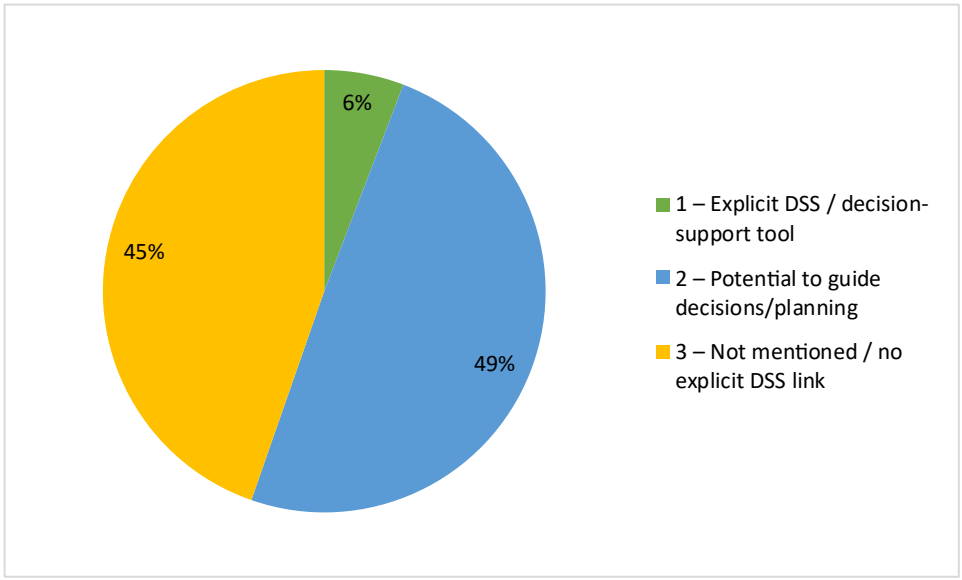


Fig. 9. Distribution of reviewed agroforestry and related land use models by level of integration into decision-support tools (DSS)

3.4. Challenges, gaps, future directions and technological advances

3.4.1. Common challenges in implementing and validating models

The reviewed literature identified four major categories of challenges in the implementation and validation of AF and related LU models (Table 4a). First, data and validation limitations are widely reported, including insufficient or low-quality driving factors and field data, limited historical records, and challenges in calibration and validation due to missing measurements and classification or parameter-setting errors (Verburg et al. 2002; Zanzi et al. 2021; Liu et al. 2024). These constraints are consistent with broader land system modelling literature, which emphasizes persistent data scarcity and uncertainty in land-use/land-cover change (LUCC) models, particularly in heterogeneous agricultural landscapes where ground truth data are expensive and temporally inconsistent (Rindfuss et al. 2004; Kindu et al. 2018; Zhong et al. 2022). Validation is further hindered when studies rely on estimated inputs, short historical records or reconstructed baselines, which increase uncertainty and limit independent ground-truth comparison. Similar concerns are raised in global integrated assessment and scenario-

based modelling, where hindcasting is often constrained by incomplete socio-environmental datasets (Voinov and Shugart 2013; Kindu et al. 2018).

Second, spatial and scale representation challenges are prominent, with models often constrained by coarse spatial resolution, geolocation inaccuracies, and mismatches between model scale and the heterogeneous nature of landscapes, making it difficult to represent complex systems (Chakir and Le Gallo 2013; Liang and Liu 2014; Groß et al. 2024). These scale mismatches are a well-known issue in land-use modelling, where grid-based approaches often fail to capture fine-scale ecological processes in AF systems (Jahel et al. 2017).

Third, model complexity and structural limitations are frequently highlighted; models tend to be computationally demanding, highly sensitive to parameter choices and conversion order, and reliant on simplifying assumptions, often resulting in outputs that are difficult to interpret (Lu et al. 2015; Lee et al. 2018). This issue is also reflected in broader ecological and environmental modelling debates, where increasing model complexity does not always improve predictive accuracy, but, often, reduces transparency and interpretability (Janová et al. 2024; Malmborg et al. 2024; Yirsaw and Nigussie 2024).

Finally, behavioral, policy and implementation-related challenges include limited representation of farmer decision-making, behavioral constraints, weak integration into policy frameworks, and insufficient incorporation of social science perspectives (Budău et al., 2023; Lacher et al., 2023; Menz & Grist, 1996; Otter & Deutsch, 2023). This limitation is widely discussed in land system science, where many models still rely on simplified rational-choice assumptions that fail to capture heterogeneous farmer preferences, risk aversion, and institutional constraints (Noël and Cai 2017; Tarfasa et al. 2018).

Table 4. Summary of common challenges faced in implementing and validating and existing gaps of agroforestry and related land use models.

a. Common challenges in implementing and validating models

Challenge category	Typical issues
Data / validation challenges	Lack or low quality of driving factor and field data, limited historical records, classification errors, and difficulties in calibration/validation (e.g., lack of detailed willingness data, missing measurements, limited long-term land-use or yield data, classification and parameter-setting errors)
Spatial / scale representation challenges	Limited spatial detail or geolocation, non-spatial formulations, sensitivity to spatial resolution and spatial mismatch, and difficulty representing complex landscapes
Model complexity, sensitivity and structural limits	Models hard to apply or time-consuming, high sensitivity to parameter choices and conversion order, incomplete understanding or coverage of interactions, linearity assumptions, and process-model outputs that are difficult to interpret
Behaviour, policy and implementation challenges	Behavioural reluctance and farm constraints, limited integration into policy, lack of social-science and communication capacity, context-specific decision-maker objectives, and lack of implementation examples

b. Existing gaps of models

Gap category	Typical issues
Data, validation and uncertainty gaps	Small or geographically limited samples, missing or restricted access to key data (tree species, willingness, landowner data), lack of long-term or detailed data, limited validation and remaining parameter or structural uncertainty
Scale, spatial and cross-system integration gaps	Limited treatment of inter-regional spillovers and trade, lack of macro-economic or cross-sector perspectives, missing spatial configuration and fragmentation, and insufficient integration of feedbacks between production, environment and broader systems
Missing processes / components or model-structure gaps	Omitted ecological or biological interactions (e.g. tree–crop processes, compartments), lack of stochastic or uncertainty modules, and structural simplifications such as deterministic models without parameter uncertainty
Economic, social or policy-relevant gaps	Absence of economic equilibrium or cost-optimal pathways, missing welfare and macro-economic analysis, gaps between expected subsidies and actual willingness, limited social data and off-farm heterogeneity, and under-representation of social factors
Other specified gaps	More specific issues such as compartment size effects not fully examined or model-specific simplifications that are not easily grouped with the categories above

3.4.2. Existing gaps of models

The review identified several recurring categories of gaps into four themes, consistently reported across the literature (Table 4b). First, data, validation, and uncertainty gaps are

642 prominent, with studies highlighting reliance on small or geographically limited datasets,
643 restricted access to key variables (e.g., species traits, landholder behavior), and insufficient
644 long-term data, alongside limited validation and persistent parameter and structural uncertainty
645 (Valbuena et al. 2010; Lee et al. 2018; Conde Salazar et al. 2021; Yadav et al. 2024). Second,
646 scale, spatial, and cross-system integration gaps are evident, including limited treatment of
647 inter-regional spillovers and trade, lack of macroeconomic or cross-sectoral perspectives, and
648 insufficient representation of spatial heterogeneity and system feedbacks (Gibreel et al. 2014;
649 Zhang et al. 2024). Third, model structure and process related gaps arise from the omission of
650 key ecological interactions (e.g., tree–crop processes), lack of stochastic components and
651 structural simplifications such as deterministic formulations (Graves et al. 2005; Paut et al.
652 2021). Fourth, economic, social, and policy-relevant gaps are widely reported, including the
653 absence of equilibrium or cost-optimal pathways, limited welfare and macroeconomic analyses,
654 discrepancies between policy incentives and farmer behavior, and underrepresentation of social
655 heterogeneity (Pontius et al. 2001; Knoke et al. 2022). Additional model-specific limitations,
656 such as compartment-size effects and simplifications that are not easily categorized, are also
657 noted (Manson 2006; Mamanis et al. 2021; Yirsaw and Nigussie 2024), while some studies do
658 not explicitly report gaps (Wang et al. 2022; Varma et al. 2024). Collectively, these gaps
659 highlight the need for next-generation modelling frameworks that integrate multi-scale data,
660 explicitly represent uncertainty, couple biophysical and socio-economic processes, and better
661 align with policy and decision-making contexts.

662 *3.4.3. Future directions for enhancing accuracy and applicability of models*

663 The reviewed literature highlighted several complementary pathways to improve the accuracy
664 and applicability of AF and related LU models (Table 5). First, enhancing data availability,
665 quality, and resolution is consistently identified as a critical priority. Expanding spatial and
666 temporal coverage, improving monitoring systems (e.g., soil, biomass, and nutrient
667 inventories), and incorporating finer spatio-temporal datasets can substantially reduce

uncertainty and strengthen model reliability (Ellis et al. 2004; Lee et al. 2018; Liu et al. 2024). Second, advances in model structure and uncertainty treatment are needed, including the integration of missing or simplified processes (such as phosphorus and potassium dynamics and management practices), improved parameter estimation, and more rigorous uncertainty analyses (e.g., Monte Carlo approaches) (Elevitch and Johnson 2020; Li et al. 2021; Yadav et al. 2024). These improvements would enable models to better represent complex AF systems and produce more robust predictions.

Beyond accuracy, increasing model applicability requires stronger integration across disciplines and decision contexts. Future models should better link biophysical, economic, and social drivers, and be coupled with tools such as GIS, visualization platforms, and complementary modelling approaches (e.g., agent-based or multi-regional input–output models) (Lu et al. 2015; Li et al. 2021; Gao et al. 2023). Embedding participatory elements and aligning model outputs with stakeholder needs can further enhance their relevance for decision-making. Additionally, extending applications across diverse regions, land-use types, and climate scenarios is essential to improve model transferability and scalability (Gibreel et al. 2014; Dang and Kawasaki 2017; Dilla et al. 2020). Finally, emerging directions emphasize the need to assess broader system outcomes, including climate suitability, ecosystem service provision and economic impacts (Conway and Wellen 2011; Applegate et al. 2022; Budău et al. 2023). Collectively, these advancements point toward a shift from data-constrained, discipline-specific models to integrated, data-rich, and decision-oriented frameworks capable of supporting sustainable land-use planning under changing environmental and socio-economic conditions.

Table 5. Summary of future research directions to improve the accuracy and applicability of AF and related LU models

Improvement category	Typical directions
Improve data availability, quality or resolution	Extend study areas, collect better or more complete data, and use finer spatio-temporal data to reduce uncertainty and improve model capacity

Refine model structure, processes or uncertainty treatment	Refine procedures and ranking metrics, add missing process modules, improve parameter estimation and uncertainty handling
Integrate models, drivers or decision-support / participatory elements	Integrate biophysical, economic and social drivers, link with GIS and visualization, couple with ABM or biophysical models, and strengthen links to decision-making and participatory approaches
Extend application scales, regions or scenario coverage	Apply models to other regions or communities, consider broader climate and land-use scenarios, add more land-use types and explore multi-scale use
Other improvement directions	Diverse model-specific suggestions, such as better linking to future climate suitability, focusing on benefits of shelter under climate warming, or examining property valuation effects

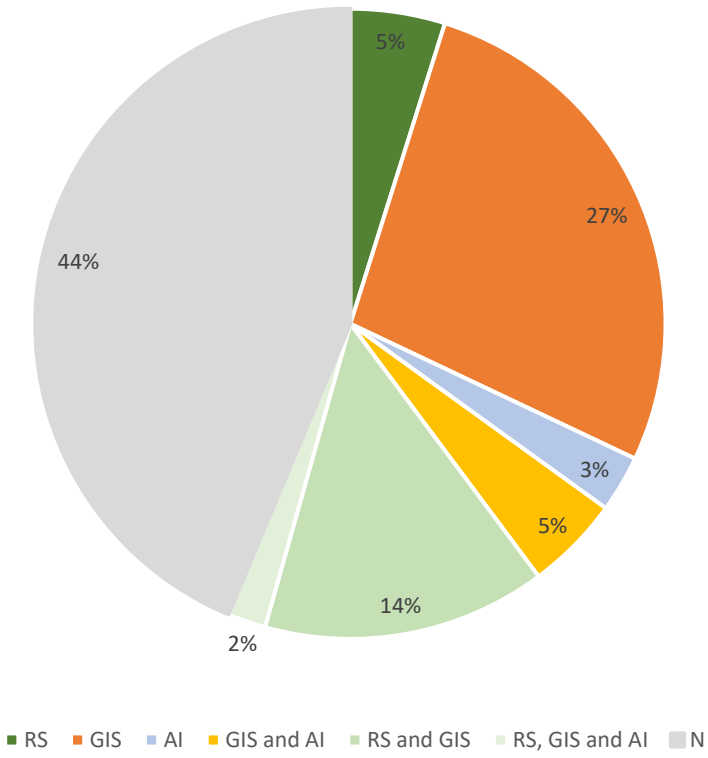
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693 *3.4.4. Role of emerging technologies in enhancing modelling*

694 The distribution of emerging roles of technologies in methodological approaches (Fig. 10)
695 showed a pronounced reliance on non- spatial and digital techniques in AF and related LU
696 modelling, which accounted for 45 (43.7%) of the reviewed studies not employing Remote
697 Sensing (RS), Geographic Information Systems (GIS), or Artificial Intelligence (AI). This
698 finding aligns with broader observations that AF and related LU research have, historically,
699 been constrained by limited access to spatial data and computational tools, particularly in
700 developing regions (Kindu et al. 2013; Desalegn et al. 2014; Temesgen et al. 2018; Assaye et
701 al. 2024). Among technology-driven approaches, GIS emerged as the most widely utilized
702 standalone tool (28 = 27.2%), underscoring its established role in spatial analysis, land
703 suitability assessment, and decision support systems (Lu et al. 2015; Mei et al. 2018). The
704 integration of RS and GIS (15= 14.6%) reflected a growing trend toward combining spatial
705 analytics with earth observation data, which have been shown to enhance landscape scale
706 monitoring, biomass estimation, and land-use classification (Sun et al. 2016; Kindu et al. 2018;
707 Lacher et al. 2023)). However, the adoption of AI remains limited, both as a standalone tool
708 (3= 2.9%) and in combination with GIS (5 =4.9%) or with RS and GIS (2 = 1.9%), despite its
709 demonstrated potential to improve predictive accuracy, automate feature extraction, and model
710 complex interactions (Zhan et al. 2019; Zhang et al. 2023). Similarly, the low uptake of RS as
711 a standalone approach (5 = 4.9%) suggests that its full analytical value is typically realized only

712 when integrated with complementary geospatial and computational tools in AF and related LU
713 modelling. The relatively small proportion of studies employing fully integrated RS–GIS–AI
714 frameworks highlights a critical methodological gap, particularly given the rapid advancements
715 in high-resolution satellite imagery, cloud computing platforms (e.g., Google Earth Engine),
716 and machine learning algorithms (Reichstein et al. 2019). Emerging technologies offer
717 substantial opportunities to enhance AF and related LU modelling by enabling multi-scale,
718 data-driven analyses, improving temporal monitoring, and supporting scenario-based decision
719 making under climate and land use change (Stetter et al. 2024; Demissie et al. 2026; Mahmoud
720 and Arabi 2026). Therefore, expanding the integration of RS, GIS, and AI is essential to
721 improve the accuracy, scalability, and adaptability of AF and related LU models, ultimately
722 supporting more resilient and sustainable land management strategies.

723



724

725 **Fig. 10.** Distribution of reviewed agroforestry and related land use models by use of emerging technologies: AI =
726 Artificial Intelligence, GIS = Geographical Information Systems, RS = Remote Sensing, N = not applicable

4. Conclusions

This review synthesizes AF and related LU models, identifying seven main categories: empirical/statistical, process-based, spatially explicit, optimization/economic, agent-based, machine learning, and integrated hybrid models. Although LU modelling is more established, AF modelling has grown significantly since 2020, reflecting increasing recognition of the role of AF in sustainable land management. Each model category provides distinct capabilities, from representing biophysical processes and spatial patterns to evaluating economic trade-offs, farmer decision-making, and future scenarios. No single approach captures all dimensions of AF and related LU systems.

Model selection should be guided by the research objective, data availability, spatial and temporal scales, and model assumptions and validation. Process-based models can assess tree–crop–soil interactions; spatially explicit models can examine land-use patterns and potential AF distribution; optimization and economic models can evaluate profitability and trade-offs; agent-based models can investigate farmer decisions and adoption; and empirical/statistical and machine-learning models can estimate relationships and predict outcomes. Integrated/hybrid models can connect complementary ecological, spatial, economic, and social processes when a broader system perspective is required. Model characteristics and components vary widely, but, generally, include input datasets, drivers, structural frameworks, and outputs, such as land use scenarios and indicators. Over time, modelling approaches have shifted from static, single methods towards more dynamic, integrated, multi-scale, and scenario-based systems that better address uncertainty and complexity.

Despite methodological advances, important challenges remain, including data scarcity, validation difficulties, scale mismatches, uncertainty, and the limited representation of social and institutional factors. Applications are concentrated at local and regional scales, while cross scale links and integration with decision-support systems remain areas for further development.

These limitations can constrain the transferability of model outputs and their usefulness for practical AF and related LU planning and policy decisions.

Future research should prioritize AF- and related LU-specific hybrid, multi-scale, and uncertainty-sensitive models, improved data integration, and stronger alignment with decision-making needs. Remote sensing, GIS, and artificial intelligence offer opportunities to improve model accuracy, scalability and real-world applicability. Researchers and practitioners should select models according to the AF and related LU system, the processes and outcomes of interest, the required spatial and temporal scales, and the availability of reliable data. Where no single approach adequately represents the relevant ecological, spatial, economic, and social dimensions, combining complementary models may provide a more comprehensive basis for sustainable land-use planning and agroforestry decision-making.

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